What Learning Analytics Reveals About Adult Students in Online Higher Education

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Abstract

Online learning has become an established part of higher education, offering flexible study opportunities that are particularly relevant for adult learners combining studies with work and family responsibilities. At the same time, digital learning environments generate detailed data that can be used to better understand student behaviour. This study examines adult students' learning in an online higher education course by combining learning analytics with survey-based self-assessments. The dataset includes pre- and post-course surveys, video viewing data, learning platform activity logs, and course performance data from 23 students. The study explores how adult learners engage with course materials, how they assess their competence before and after the course, and how activity patterns relate to performance. The results show considerable variation in study behaviour, with activity concentrated around deadlines and weekends. Students initially assessed their competence critically, particularly in data analytics, but reported clear improvement by the end of the course. Initial self-assessments did not appear to clearly predict course success. The findings suggest that learning analytics can provide useful insights into adult learners' engagement and progression, but its interpretive value depends on course design, assessment practices, and the technical implementation of the learning environment.

Keywords: learning analytics, adult students, online higher education, online learning, student experience

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Introduction

Learning analytics (LA) refers to the collection, analysis, and use of data generated in learning environments to understand and support learning and improve teaching practices. In online higher education, learning analytics has become increasingly relevant because digital platforms make it possible to track a wide range of student activities, including video viewing, quiz completion, logins, task submissions and participation patterns.

Previous research has shown that learning analytics can help identify behaviours associated with course continuation and completion. For example, the number of videos watched has been linked to successful course completion (de Barba et al., 2016; Pursel et al., 2016), and rewatching videos has been associated with a lower likelihood of dropping out (Sinha et al., 2014). Quiz completion has also been found to be an important predictor of course completion, especially in the early and middle stages of a course (Ramesh et al., 2014), while high quiz scores may further increase the likelihood of finishing a course successfully (Jiang et al., 2014).

At the same time, online learning is shaped by more than measurable activity alone. Students' experiences of course structure, interaction, feedback, flexibility, and assessment all influence engagement and perceived learning. Earlier studies have shown that students value teachers' pedagogical competence, clear guidance, social presence, and transparent assessment practices in online learning environments (Mäkipää et al., 2022). Students have also reported that well-designed courses, strong motivation, confidence in using digital tools, and good self-regulation skills support successful online learning (Haarala-Muhonen et al., 2025; Masiello et al., 2024; Viberg et al., 2020).

For adult learners, these questions are particularly important. Adult students often combine studies with employment and other responsibilities, which may shape when and how they participate in online learning. Yet research focusing specifically on how learning analytics reflects the study practices and self-assessments of adult students in online higher education remains relatively limited.

This paper examines adult students' study practices in one online higher education course by combining survey-based self-assessments with system-generated learning analytics. The study focuses on three questions:

1. What does learning analytics reveal about adult students' study practices during an online course?
2. How do adult students assess their competence before and after the course?
3. How do students' activity patterns and self-assessments relate to course performance?

By addressing these questions, this study contributes to a more practice-oriented understanding of how learning analytics can support course design and interpretation in adult online higher education.

Background

Research on learning analytics has often focused on predicting course completion, identifying at-risk learners, and modelling activity patterns in digital learning environments. Log data has been a particularly common source of evidence, while recent reviews have also highlighted the growing role of dashboards, feedback processes, and more advanced analytic methods (Masiello et al., 2024; Palanci et al., 2024). At the same time, scholars have emphasized that analytics alone cannot capture all relevant dimensions of learning. Motivation, metacognition, emotions, and self-regulated learning remain important but are often only partially visible in system data (Masiello et al., 2024).

In online higher education, video use has attracted considerable attention. Watching lecture recordings and instructional videos has repeatedly been associated with successful participation and course completion (de Barba et al., 2016; Haarala-Muhonen et al., 2025; Pursel et al., 2016). However, participation in online discussions has produced more mixed findings, with some studies linking forum activity to successful completion and others suggesting that it may also signal struggle or disengagement (Pursel et al., 2016; Ramesh et al., 2014). This underlines the importance of interpreting analytics data cautiously and in context.

From the student perspective, online learning is influenced not only by available materials but also by teaching practices and course design. Students have identified clear guidance, pedagogical quality, interaction, flexibility, and timely feedback as central conditions for successful online learning (Haarala-Muhonen et al., 2025; Kuluşaklı, 2025; Mäkipää et al., 2022). In addition, self-regulated learning skills such as planning, monitoring, and evaluating one's learning have been shown to support academic success in online environments (Masiello et al., 2024; Viberg et al., 2020).

For adult learners, flexibility may be particularly significant, as online study often takes place alongside work and family responsibilities. This makes it useful to examine not only performance outcomes but also patterns of timing, engagement, and self-assessed competence. In that sense, combining learning analytics with survey-based student perspectives can provide a richer understanding of adult students' study practices than either source alone.

Method

Research Context

The study examined one online higher education course, *The Practice of Knowledge Management* (3 ECTS), implemented between 7 January and 27 February 2026 in open higher education (Open University of Applied Sciences). The course content focused on the basics of data analytics, the use of Power BI, and the visual presentation of reports from a graphic design perspective. The course materials consisted mainly of written instructions produced by the teachers, lecture videos, links to online materials, and examples of visualizations created with Power BI.

Course completion was based on assignments and Moodle-based assessment tasks. In addition to tasks based on learning materials, students completed analysis of a public visualization and self-assessment related to a visualization they had produced themselves.

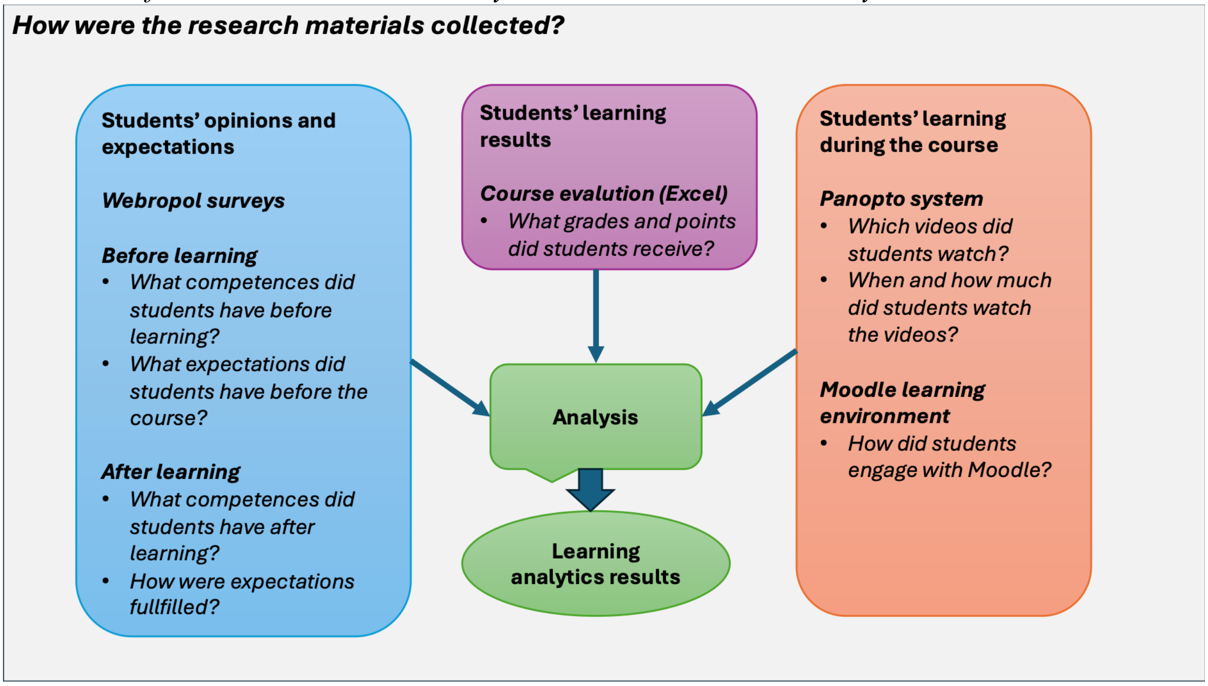
Data Sources

The study combined four sources of data:

1. a pre-course Webropol survey on students' self-assessed competence,
2. Panopto video-viewing data collected during the course,
3. Moodle activity log data and course performance data, and
4. a post-course Webropol survey on students' self-assessed competence.

The overall analytical idea is illustrated in **Figure 1**.

Figure 1
Overview of Data Collection and Analytical Tools Used in the Study



The pre-course survey was distributed several months before the course started. Thirty-one respondents answered this survey, but not all of them later participated in the course. The main course dataset consisted of the 23 students who completed course work and thus generated activity data in Moodle and Panopto as well as course points and grades. In addition, 30 students had logged in to the learning platform, while 23 of them watched the Power BI videos. As a result, different parts of the analysis are based on partially overlapping but not identical subsets of participants.

Variables and Analytical Approach

The study used a descriptive case-based design and can be characterized as a descriptive case study combining survey data and learning analytics. The purpose was not to build predictive statistical models but to examine what kinds of insights can be gained by combining self-assessment data with learning analytics in one adult online learning context.

The key variables were as follows:

- *self-assessed competence*, measured before and after the course on a scale from 0 to 5 in three broad content areas: knowledge management theory, the basics of data analytics, and analytics-related applications.
- *activity*, referring to actions recorded in Moodle logs.
- *video engagement*, referring to Panopto viewing time and number of views.
- *course performance*, measured through assignment points and final course grades.

The maximum number of assignment points in the course was 100. Final grades were given on a scale from 0 to 5. Because the surveys and the course participation data did not include exactly the same respondents, survey results are interpreted as indicative rather than strictly matched measures at the individual level.

The data were analysed descriptively, and the results were visualized using Power BI.

Results

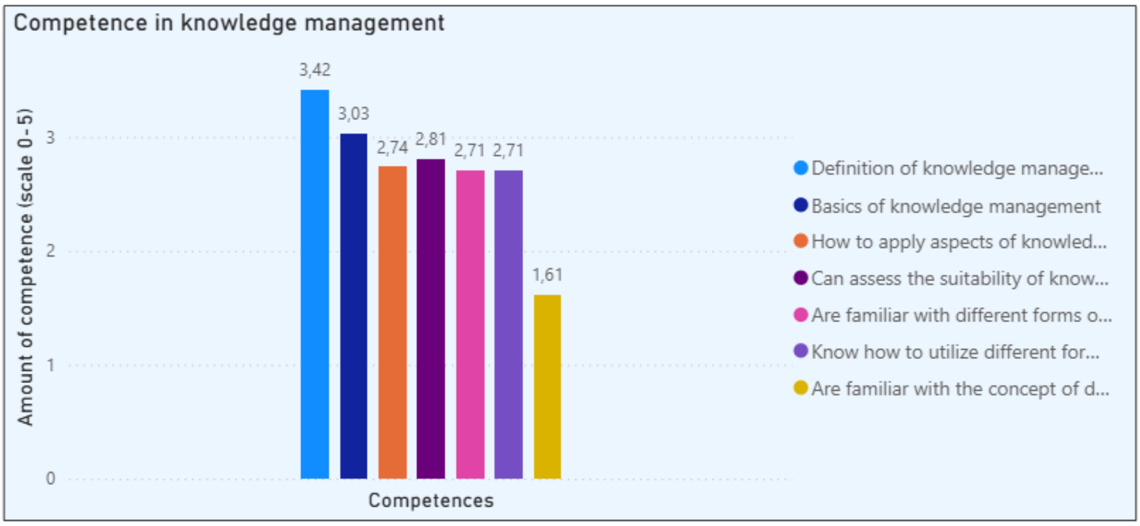
Students' Self-Assessed Competence Before the Course

Before the course, students were asked to assess their competence in three areas: knowledge management theory, the basics of data analytics, and analytics-related applications. Overall, students rated their starting competence relatively modestly. On average, self-assessed competence was 2.76 in knowledge management theory, 1.80 in the basics of data analytics, and 2.24 in analytics-related applications. Students also estimated that they would spend an average of 7.1 hours per week on the course.

The baseline results suggest that students felt more confident about knowledge management as a conceptual area than about data analytics. The lowest ratings were found in topics related to analytics concepts and tools, especially more advanced or less familiar applications. By contrast, commonly used tools such as Excel were rated more positively. Overall, the pattern indicates that students entered the course with uneven but generally cautious assessments of their competence.

A summary of the baseline self-assessments is presented in **Figure 2**.

Figure 2
Students' Self-Assessed Competence Before the Course Across the Three Main Content Areas



Student-level variation was considerable. Some students rated themselves consistently low across all three areas, while others reported more selective strengths. The baseline data therefore suggest not only low average confidence in analytics-related topics but also substantial heterogeneity among adult learners entering the course.

When initial self-assessments were compared with final course grades, students' starting perceptions of their own competence did not appear to correspond closely to later course success. Most students rated their initial competence rather low, yet this did not prevent successful course completion. This finding suggests that low initial confidence should not automatically be interpreted as low potential for success in adult online learning.

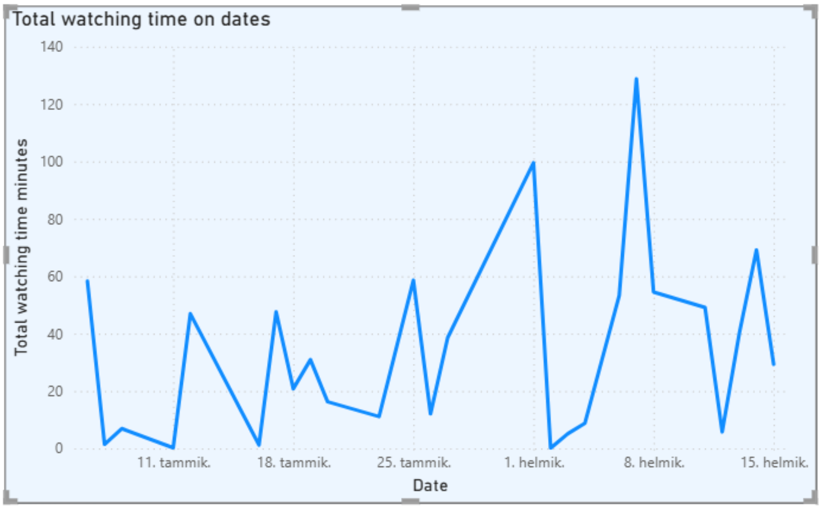
Learning Analytics During the Course

The course included five instructional videos related to the use of Power BI, with a total duration of 47.17 minutes. Across the course, students accumulated 895 minutes of viewing time and 131 viewing events. The average video length was 9.4 minutes, while the average viewing time per student was 38.9 minutes. On average, students generated 5.7 viewing events each, which is close to the number of available videos.

Video-viewing patterns varied substantially across students. Some students watched clearly more than the total duration of the provided video material, suggesting repeated viewing of selected videos, while others watched substantially less. A middle group viewed approximately the equivalent of the full video offering once. This pattern indicates that adult students used the videos in different ways: some appeared to revisit content repeatedly, while others seemed to use the videos more selectively.

In terms of timing, video engagement increased toward the later part of the course and peaked as the Power BI assignment deadline approached. Activity was also concentrated on weekends, which may reflect the study rhythms of adult learners combining studies with work and other responsibilities. This temporal pattern is shown in **Figure 3**.

Figure 3
Video Viewing Activity Over the Duration of the Course



At the level of individual videos, some variation was also visible. The most substantial viewing time was associated with videos that addressed central Power BI functions rather than introductory installation guidance. This suggests that students particularly engaged with those parts of the material that were most directly connected to task performance, although this interpretation should be treated cautiously and remains tentative.

In addition to video data, student activity was examined through Moodle log entries. Moodle activity showed clear variation over the course timeline. Activity was high at the beginning of the course, then declined during the middle phase, and rose again around major submission points. This pattern is likely related to the course structure: once students moved more intensively into Power BI practice, a larger share of their work took place outside Moodle, making some learning activity less visible in the platform log.

A further practical observation emerged from the Moodle data: the usefulness of analytics depends strongly on how the learning environment has been designed. In this course, the Moodle implementation did not fully support more detailed analytics interpretation. As a result, activity could be measured at a general level, but not always in a way that would allow fine-grained conclusions about specific learning behaviours. This is an important design issue for future course development.

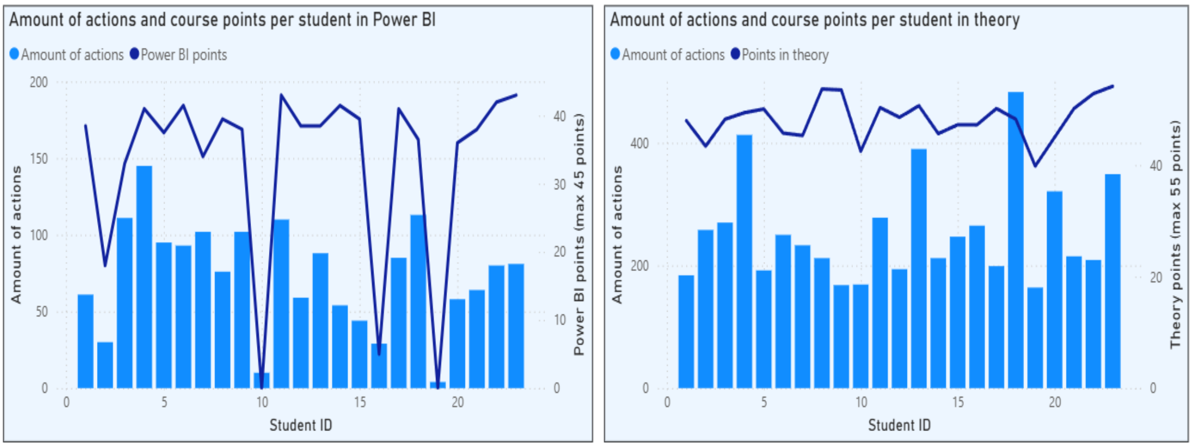
Activity and Course Performance

When Moodle activity was compared with students' assignment points, no clear overall relationship was observed in the descriptive analysis. Students differed considerably in their recorded activity, but the point distribution remained relatively high for most students. This may partly reflect the assessment structure of the course: when most students receive relatively strong scores, the point scale does not differentiate performance clearly enough to reveal strong patterns.

A more detailed comparison, however, suggested that the relationship between activity and performance differed across content areas. In the theoretical knowledge management part of the course, students generally performed well regardless of their visible Moodle activity. In the Power BI section, lower activity seemed more often to coincide with weaker task performance, although there were also students who performed well with relatively little recorded Moodle activity. One plausible interpretation is that prior experience with Power BI or similar applications may explain some of this variation.

This comparison is summarized in **Figure 4**.

Figure 4
Moodle Activity and Task Performance in the Power BI Section and the Knowledge Management Theory Section



Taken together, these results suggest that analytics related to technical application learning may be more directly interpretable than analytics related to more conceptual course content. At the same time, the results also underline that recorded platform activity does not capture all relevant learning effort.

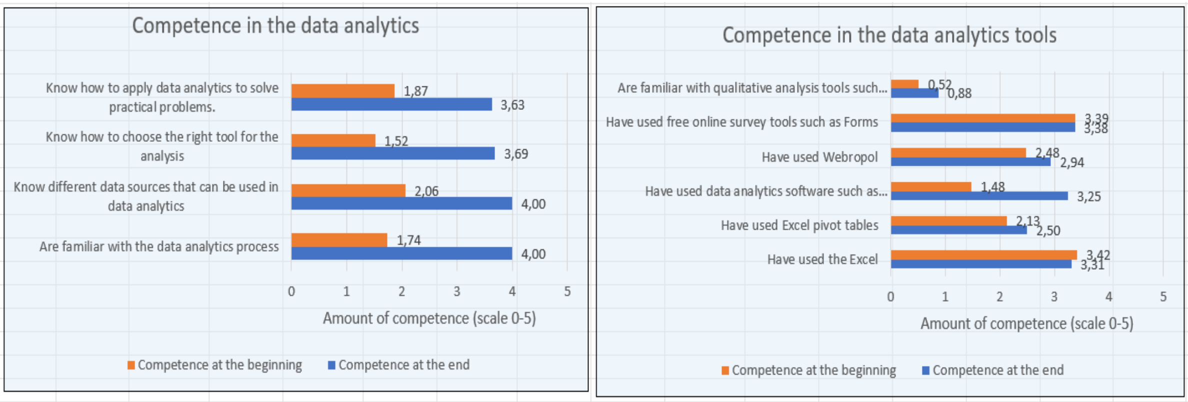
Students' Self-Assessed Competence After the Course

At the end of the course, students again assessed their competence in the same three areas. Across all content domains, self-assessed competence increased from the pre-course level. Students thus perceived that they had learned during the course.

The strongest increase was found in the basics of data analytics, where the mean self-assessment rose from 1.80 to 3.83. In knowledge management theory, the mean increased from 2.76 to 3.85. In analytics-related applications, the increase was more moderate, from 2.24 to 2.71 overall. This more limited change is understandable, given that the applications category included both familiar tools such as Excel and less familiar tools such as Power BI. Within that category, the most notable perceived improvement concerned Power BI, which was a major focus of the course.

The overall before-and-after comparison is shown in **Figure 5**.

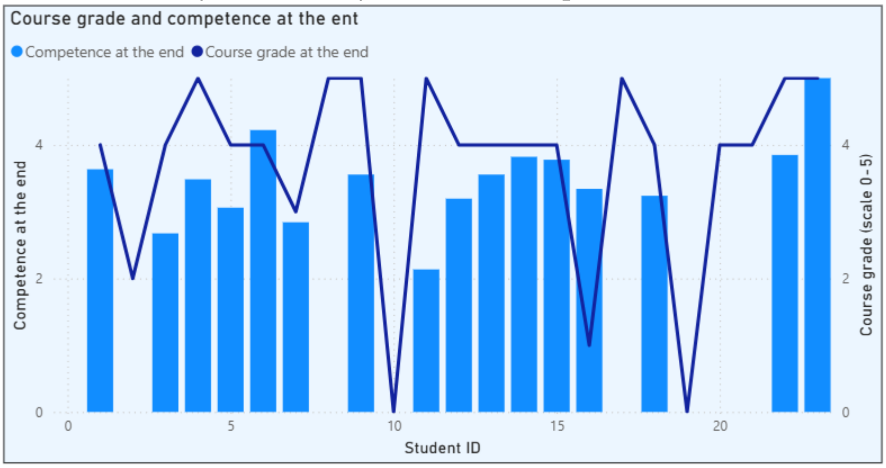
Figure 5
Students' Self-Assessed Competence Before and After the Course Across the Three Main Content Areas



When end-of-course self-assessments were compared with final grades, students' views of their own competence appeared less critical than at the beginning of the course. Even so, self-assessed competence still tended to remain somewhat lower than formal course grades. This suggests that students became more confident through the course, but many still judged their own competence conservatively.

A more detailed comparison of end-of-course self-assessment and final grades is presented in **Figure 6**.

Figure 6
Students' End-of-Course Self-Assessed Competence in Relation to Final Course Grades



Discussion

The contribution of this study lies in combining learning analytics with self-assessed competence in an adult learning context. The study examines what learning analytics reveals about adult students in online higher education when system-generated data is combined with students' own competence assessments. Three main observations can be identified.

First, students entered the course with relatively cautious views of their competence, especially in data analytics and analytics-related applications. This is an important finding. Adult learners may begin online courses with lower confidence than their later performance would suggest. In this case, students' initial self-assessments did not clearly correspond to eventual course success. This implies that low starting confidence should not be interpreted too quickly as a sign of limited ability.

Second, learning analytics made visible substantial differences in study practices during the course. Students varied in how much video material they watched, when they studied, and how much activity appeared in the Moodle log. Weekend peaks and deadline-related surges suggest that flexibility is central in adult online learning. This supports earlier research emphasizing the importance of flexible course design, self-regulation, and teaching practices that accommodate different participation rhythms (Kuluşaklı, 2025; Viberg et al., 2020).

Third, the study shows both the value and the limits of learning analytics. Analytics data offered useful insights into activity patterns, engagement with video materials, and broad relationships between platform activity and task performance. At the same time, the interpretive power of analytics remained dependent on course design and technical implementation. Not all meaningful learning activity becomes visible in platform logs, and weak differentiation in course assessment can make it difficult to identify clearer relationships between engagement and success.

The findings also have pedagogical implications. In this case, learning related to technical application use, especially Power BI, appeared more visible in course activity and performance patterns than learning related to more conceptual content. This may suggest that technical skills produce clearer behavioural traces and performance distinctions in online environments. However, this should be interpreted as a contextual observation rather than a universal rule.

More broadly, the results suggest that learning analytics is most useful when it is integrated into course design from the beginning. If teachers want to use analytics meaningfully, they need to consider not only what can be measured, but also how the structure of the course, the assessment model, and the learning environment shape what becomes visible in the data. The findings should be interpreted as context-specific observations rather than generalizable conclusions.

Limitations

This study has several limitations. First, it is based on one course and a relatively small group of students, which limits the generalizability of the findings. Second, the pre-course and post-course survey respondents did not fully overlap with the students who generated course activity data, so the self-assessment results should be interpreted as indicative rather than as fully matched longitudinal measures for every participant. Third, the analysis was descriptive rather than predictive or inferential, which means that the results identify patterns but do not establish causal relationships. Fourth, the Moodle implementation did not support more fine-grained interpretation of analytics, which restricted what could be concluded from the platform data.

Despite these limitations, the study demonstrates how combining analytics with student self-assessment can provide a useful, practice-oriented perspective on adult online learning.

Conclusion

This study examined adult students' online learning in one higher education course by combining survey-based self-assessments with learning analytics derived from Moodle and Panopto. The results show that students assessed their initial competence rather critically, especially in data analytics and analytics-related applications, but reported clear improvement by the end of the course. Initial self-assessments did not appear to clearly predict course success.

Learning analytics revealed substantial variation in study practices during the course. Students differed in how much video material they watched and how actively they used the learning platform, and study activity was concentrated particularly around weekends and deadlines. At the same time, the study showed that the interpretive value of analytics depends heavily on course design, assessment structure, and the technical implementation of the learning environment.

For higher education teachers, the findings suggest that learning analytics can support understanding of adult students' engagement and progression, but only when interpreted in context. Analytics should therefore be seen not as a self-sufficient measure of learning, but as one source of evidence that becomes most useful when combined with pedagogical judgment and student perspectives.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The authors declare that ChatGPT (OpenAI), an AI-assisted writing software, was used in proofreading and refining the language used in the manuscript. The usage was limited to correcting grammatical and spelling errors and rephrasing statements for accuracy and clarity. The authors further declare that, apart from ChatGPT (OpenAI), no other AI or AI-assisted technologies have been used to generate content in writing the manuscript. The ideas, design, procedures, findings, analyses, and discussion are originally written and derived from careful and systematic conduct of the research.

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